ADAPTING HUMAN LEADERSHIP APPROACHES FOR ROLE ALLOCATION IN HUMAN-ROBOT NAVIGATION SCENARIOS

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ABSTRACT

In this paper, we propose to examine the practices of leadership defined in human relationships and model their use in maximizing performance for human-robot interaction scenarios. This process involves first defining the human-robot space of interaction and mapping the situational context in which human leadership styles are most fitting. We then determine which behavior, for both the human and robot, is most appropriate in order to understand the proper roles for human-robot integration. From there, we model the necessary robot behavior for increasing efficiency in human-robot interaction schemes. We conclude by discussing experimental results derived from allocating roles in representative human-robot navigation scenarios.

1. INTRODUCTION

As the symbiotic relationship between humans and robots solidifies, robots are transitioning from functioning solely in the research environment to becoming productive team members in society. As such, research in human-robot interaction and the proper roles (or behaviors) for integration become increasingly important. The first formal research in role allocation for human-machine scenarios is addressed in [1], in which decisions between machine versus human control are made based on a simple comparison of capabilities. Earlier work is also found in [2] in which human and machine capabilities are scaled in order to determine when role transitions should occur. Olsen and Goodrich [3] develop a model to allocate roles in human-robot interaction schemes based on assessment of the number of robots a single individual can control in a given scenario. In [4], a human-centered approach is used to understand the role of human-robotic teamwork in future human space exploration missions. In this work, a framework is developed in which robots become functional tools that assist the human rather than replace the human operator. In [5,6], the focus is to change roles by dynamically adjusting the autonomy of an intelligent agent based on human physiological responses [5] and reasoning about the costs of decisions [6]. Role allocation in human and robot teams is proposed in [7,8] using an analytical framework that decomposes tasks into independent functional primitives and determines roles by evaluating system performance. In [9-12], researchers have presented complementary taxonomies that define various types of roles for enhancing the interaction between humans and robots. Finally, recent work presented in [13], discusses performance tradeoffs in incorporating collaborative task roles for systems focused on humans interacting with aerial robotic vehicles.

Although previous research and schemes provide a paradigm in which to engage robots within our society, to further understand the role of robots, we can look at the practices of leadership defined in human relationships. Different styles of leadership have been adopted to model the interaction of leadership within the organization [14-16]. Among these are directive, transactional, transformational, and empowering leadership. We can use these leadership approaches, and the practices that surround them, to provide insight into the processes we can adopt to engage our robot partners in the future.

In this paper, we discuss the adaptation of a paradigm pertaining to human leadership in organizations to the arena of human-robot interaction. Specifically, we classify possible scenarios involving human-robot navigation tasks and correlate them with scenarios that involve interaction only between humans. We propose that to maximize navigation efficiency in a particular human-robot interaction scheme, a leadership style should be employed that mirrors the leadership style that would be used if only humans were involved. Moreover, high-level behaviors that both human and robot should exhibit must be exhibited to maximize performance of the human-robot teaming arrangement. Through this process, we aim to provide a basis in which to improve our approaches for human-robot team interaction within the environment [8].

2. LEADERSHIP STYLES IN HUMAN INTERACTION SCENARIOS

The role of leadership in human relationships has permeated throughout both the academic and business communities. Investigation of the derivation of leadership, as well as its practice and utilization, has enabled humans to increase their productivity and successfully interact with others throughout their daily lives. Although there are a number of typologies that provide a framework for classifying leadership patterns, the dominant types include directive, transactional, transformational, and empowering leadership [14]. Table I provides a representational diagram of these leadership styles and their use in human organizations.

As depicted in Table I, directive leadership influences human behavior by relying on aspects of command-and-control. The utilization of directive leadership is typically based on legitimate power in which the leader occupies a higher position in the organizational hierarchy. Transactional leadership involves using the concept of personal and material rewards to motivate subordinates to achieve higher performance. By aligning subordinate contribution to equitable returns, performance can be appropriately aligned to the goals of the organization. Transformational leadership focuses on providing a global vision to unify disconnected tasks and individuals into achieving a common goal. Through transformational leadership, subordinates are motivated to increase productivity for the common good. Empowering leadership focuses on transitioning subordinates from dependency on supervisory direction to self-driven behavior. Leaders accomplish this practice by engaging all individuals in teamwork behavior as well as encouraging self-improvement and self-leadership.

In [17], the concept of the socio-technical system was established to formalize the reciprocal interrelationship between humans and machines. The theory states that humans can be made to adjust to technologies and technologies can correspondingly be made to adjust to humans. Following this theoretical vein, we elect to capitalize on the large body of research focused on human organizations and transplant the theories to the human-robot interaction space. In this manner, we can use understood practices of human leadership to adjust robot technologies to respond to the familiar ways in which humans comfortably can embrace these technologies.

Leadership Style	**Role of Leader**	**Situational Context**
Directive	• Issue Commands • Assign Goals	• Crisis Situation Subordinates are new to task
Transactional	• Monitor Performance • Provide rewards	• Need to assess and dispense awards for performance
Transformational	• Provide Vision	• Need to change course of action • Need to unify group around long-term purpose
Empowering	• Encourage teamwork, self-leadership, and development	• Need to develop new leaders • Need to draw on subordinate's knowledge

Table I: Overview of leadership styles in human organizations [15]

3. LEADERSHIP STYLES IN HUMAN-ROBOT INTERACTION

To understand the role human leadership styles play in human-robot interaction scenarios, we must first define the human-robot space of interaction and map the situational context in which each leadership style is most appropriate. We must then determine which behavior, for both the human and robot, is most appropriate. From there, we can draw on the wealth of knowledge in the robotics research arena to determine techniques to enable the necessary robot behavior for increasing performance in human-robot navigation scenarios.

We define a human-robot navigation scenario based on two dimensions – the goal and the task. The goal defines the solution to a problem. In organizational scenarios, the goal is similar, in nature, to measurable results. The task defines the actual steps required to achieve the goal. In human organizations, this is defined as the actual job assignment. Each of these dimensions has unique attributes. Task attributes have the following characteristics:

- ***Known/Unknown:*** A known task is one in which both the inputs needed to perform the task are defined, and progress toward goal achievement (output/results) can be measured. An unknown task is one in which either parameter (input or output) cannot be determined. For example, a robot traversal task in which the robot must traverse from a known initial position to an identifiable goal position is classified as *known*. In this case, the robot can compare starting and ending criteria to determine if the traversal task is near completion. In the *unknown* case, a robot traversal task can be defined in which the goal position is undetermined at task startup (for example, a buried landmine located at an unknown target position). In this case, the robot cannot directly determine whether it is making satisfactory progress toward achieving the goal.
- ***Individual/Collaborative:*** An individual task is one in which an agent can perform a task (though it might be a collective sequence of tasks) without requiring assistance from any other agent. A collaborative task is one in which an agent requires additional assistance from another agent to perform their individual task. For example, a robot navigation task in which the robot is required to locate a specified rock by navigating within a specified terrain region is classified as *individual*. If the robot requires the assistance of another robot to then transport the specified rock to another location, the associated task is classified as *collaborative*.

Goal attributes have the following characteristic:

- ***Time Critical/Available:*** A time-critical goal is one in which results must be achieved in as minimal time as possible. For example, a robot exploration task in which the robot must find sources of energy to maintain its power becomes time-critical when its batteries are near depletion. A time-available goal is one in which time is not a stringent resource constraint on achieving results such as a robot exploration task with resources of unlimited solar power.

3.1. Situational Context of Leadership Style

Based on the attributes that define human-robot navigation scenarios, we now analyze the situational context in which leadership styles can be mapped to the human-robot interaction space. Table II shows the descriptive relationship between situational context and the human-robot interaction space. Using this relationship, we can define the mapping between leadership styles and the attributes that define human-robot navigation scenarios, as shown in Table III.

Situational Context	**Human-Robot Interaction Space**
Directive • Crisis Situation • Subordinates are new to task	• Goal must be achieved in critical time • Tasks must be taught to robot agent before implementation
Transactional • Need to assess/dispense awards	• Goal is divisible into individual tasks • Tasks are achievable by individual robot agents
Transformational • Need to change course of action and unify group around long-term purpose	• Tasks are collaborative • Goal achievement can be monitored by individual agents
Empowering • Need to develop new leaders • Need to draw on subordinate's	• Agents require information from others to determine goal achievement • Tasks are collaborative and may rely on individual

knowledge	heterogeneous robot agents

Table II. Situational Context of Leadership Style

		Directive	Transactional	Transformational	Empowering
Goal	Time Critical	X			
	Time Available		X	X	X
Task	Known	X	X	X	
	Unknown				X
	Individual	X	X		
	Collaborative			X	X

Table III. Leadership styles mapped to human-robot navigation scenarios

From Table II, we see that a human-robot navigation scenario that has a time-critical goal and a known set of tasks to achieve the goal correlates to a crisis situation in which the leader is responsible for issuing commands (or tasks). Thus, such a human-robot navigation scenario can be implemented more effectively by using practices from directive leadership. On the other hand, if the goal is time-critical, but the task steps are unknown, the best one can do is to combine elements of directive and empowering leadership to achieve success.

3.2 Leader and Follower Behavior

We assume that the leadership position in human-robot navigation scenarios is always held by the human agent, and as such, the robot, in all cases, acts as the follower. Table IV combines the role of the leader defined for the different leadership styles, and highlights the corresponding role of the robot follower.

Leadership Style	Human Leader Behavior	Robot Follower Behavior
Directive	• Issue Commands • Assign Goals	• Follow commands issued by leader
Transactional	• Monitor Performance • Provide rewards	• Select the best task/goal that provides the highest reward (i.e. maximize reward function)
Transformational	• Provide Vision	• Determine if task behavior is consistent with goal • Maximize individual performance, while minimizing conflict with others
Empowering	• Encourage teamwork • Encourage follower leadership and development	• Select tasks which maximize performance of overall team (i.e. if another robot has a higher performance value for task, do not select) • If failing to perform task, ask team-member for assistance • If do not have skills to perform a task, learn new capability from leader or team-member

Table IV. Human and robot behavior associated with leadership styles

Given the role of the robot subordinate, we can draw on the wealth of knowledge in the robotics research arena and identify techniques (as well as challenges) that enable the necessary robot behaviors. In this paper, we will discuss and compare the directive and transactional leadership styles.

4. EXPERIMENTAL RESULTS

4.1 Experimental Setup

To test the theory presented on leadership styles in human-robot navigation scenarios, we utilize HumAnS-3D (Figure 1), a 3D virtual test environment that has been developed to allow human access to a virtual representation of the world and control of a virtual robot [18]. The control panel on HumAnS-3D allows the human operator to directly command the robot to move forward, backward, and turn either left or right. The graphical user interface also connects the virtual robot, viewable by the human user, to the real robot for seamless integration with the real world environment. Our assumption is that given the difference situational contexts, performance, as defined in [8] (i.e. a function of workload on the human operator and time required to complete a task) will be maximum if the appropriate leadership style is employed.

4.2 Modeling Directive Leadership

In the directive leadership scenario, a robot subordinate follows commands issued by the human leader. To model directive leadership, a human user is required to directly command the robot behaviors through tele-operation via the HumAnS-3D interface.

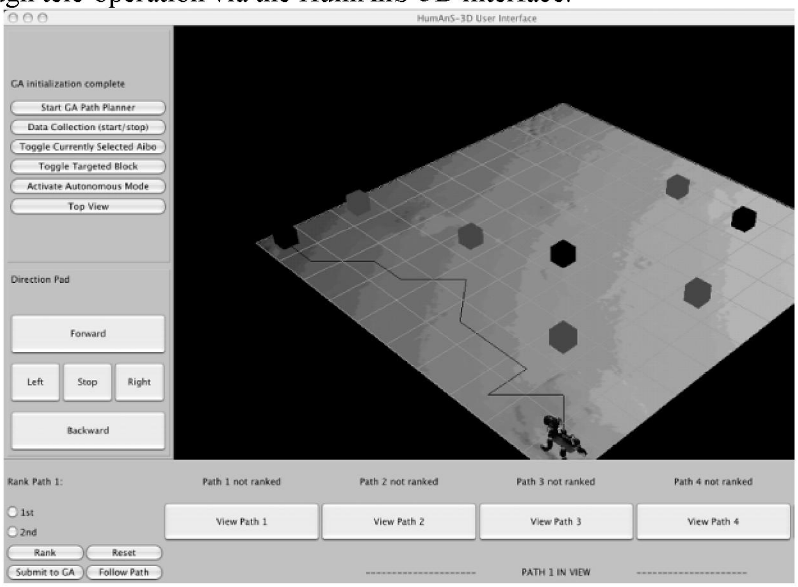


Figure 1. HumAnS-3D environment depicting virtual robot

4.3 Modeling Transactional Leadership

In the transactional leadership scenario, a robot subordinate selects the best task corresponding to the highest reward. It is the role of the human leader therefore to provide rewards that correspondingly guide the robot to a desired goal solution. A technique to facilitate selection of correct robot behavior in transactional leadership scenarios is genetic, or evolutionary, algorithms. Genetic algorithms are an adaptive method in which a search is performed to find a set of behaviors that maximize an objective function [19]. In human-robot navigation scenarios, the objective function can be defined by the human leader in order to guide the robot to the desired goal solution.

To model the transactional leadership style within the domain of human-robot interaction, an action-reward structure must be provided that is built upon a lower level communication scheme. Using a traditional genetic algorithm would imply an action-reward behavior, but communication between the human user and the robotic agent would be minimal. In traditional genetic algorithms, a user would provide a fitness function and the algorithm, after several generations, would develop solutions to maximize fitness according to the provided fitness function. Though this may be perceived as an action-reward type interaction, its rigid nature leads it away from being a good model for transactional leadership. Hence, our proposed solution is a genetic algorithm whose fitness function varies in real time and in accordance with a human leader's desires. This avoids reprogramming fitness functions whenever the human leader desires to attain a solution in an unforeseen manner.

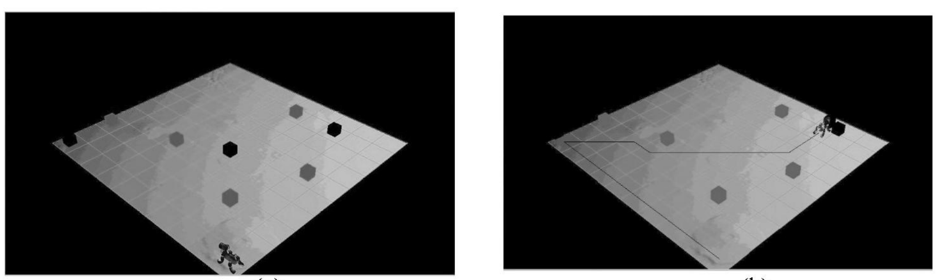
In our application, the genetic algorithm begins with a pseudo-random initialization of 10 chromosomes (a solution path) consisting of 20 genes (a grid point in the environment). The fitness function for finding an optimal solution is built on a combination of three functions. One function provides a measure of how well a path reaches a desired target. The second provides a measure of how well a path minimizes the distance traveled in reaching a desired target and the third function measures how much of the environment is traversed, irrespective of the target. During the initialization stage, each function is weighted equally to determine fitness. Through operator use of the HumAnS-3D interface, however, these weights are altered as a function of user feedback. The concept is that user preference would allow the fitness standard to be dynamically allocated in real time.

For implementation, the system runs through iterations of the genetic algorithm, and displays the five highest ranked paths to the user. The user then selects what they consider their top two choices. The associated chromosomes are then reinserted into a completely new gene pool of a new instance of the genetic algorithm. Hence, on the next run, convergence occurs at a faster rate and an optimization function based on the statically weighted fitness function is designed. By introducing this human-in-the-loop implementation, the user, in essence, acts as the dynamic portion of the fitness standard.

4.4 Test Results

To validate our adaptation of the leadership paradigm, we execute the directive and transactional leadership styles under different scenarios and then compare the corresponding performance metrics for each experimental set. Workload was determined by using the NASA TLX subjective assessment method[1] [20] and task performance was determined by monitoring execution time.

In each scenario, the mission defined for the human-robot team is as follows. There are 5 obstacle blocks and 3 target blocks located within the environment (Figure 2a). The environment is defined by a 10x10 grid, with one block (target or obstacle) randomly positioned in one of the grid cells. The user is required to visit the 3 target blocks while avoiding the 5 obstacle blocks (Figure 2b). The human must implement the task under the 4 scenario types: directive/time critical, transactional/time critical, directive/time available, and transactional/time available. For the directive/time critical and transactional/time critical scenarios, the human is told that the task must be completed within 4 minutes. For the directive/time available and transactional/time available scenarios, the human is provided unlimited time to complete the task.



(a) (b)

Figure 2. (a) Environment at task initialization. (b) Environment at task completion.

For the directive leadership style, the human directs the robot by directly controlling the movement of the robot using the available Forward, Back, and Turn buttons on the HumAnS-3D interface. For the transactional leadership style, the human directs the robot by providing direction to the robot via path suggestions. In this case, the top five paths computed by the genetic algorithm are provided as input to the user, and the user selects the two best paths for navigation.

[1] The NASA TLX subjective assessment method measures the relative importance of six factors (mental demand, physical demand, temporal demand, effort, performance, frustration level) in determining how much workload a human experiences during task implementation.

We ran through each scenario with our human participation set and recorded task execution times. After each experimental run, we also provided the NASA TLX questionnaire to the human operators to assess workload (i.e. stress on the human operator). The normalization of the execution times for each of the users was then computed such that:

$$\rho_{h,n} = ExecutionTime(h,n) \qquad NormalizedExecutionTime\ (h,n) = \frac{\rho_{h,n}}{\sum_{i=1}^{k}\sum_{j=1}^{s}\rho_{i,j}} \tag{1}$$

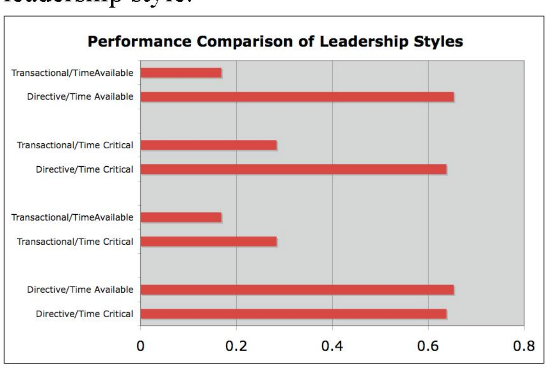
where n designates the current scenario run, s designates the number of total runs, h designates the human participant, k designates the total number of participants, and *ExecutionTime* is the execution time associated with run n and human participant h.

In addition, the normalization of workload values computed from the NASA TLX workload assessment method was calculated such that:

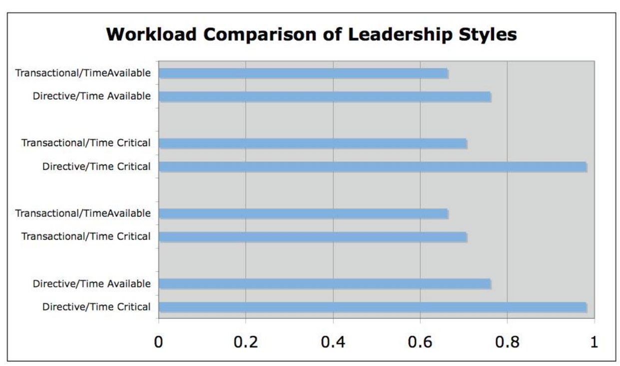
$$\omega_{h,n} = Workload(h,n) \qquad NormalizedWorkload(h,n) = \frac{\omega_{h,n}}{\sum_{j=1}^{s}\omega_{h,j}} \tag{2}$$

where *Workload* is the workload values computed from the NASA TLX questionnaire associated with human participant h and run n.

In Figure 3, we compare the performance and workload values computed for the four scenarios. Performance, in this case, is computed as *(1 – NormalizedExecutionTime),* which associates faster implementation times with better performance. As we see from Figure 3, the directive leadership style correlates to faster execution times than the transactional leadership style, but results in higher workload on the human operator, which is perhaps the greatest contributor to human error in many systems [21]. In directive leadership scenarios, a faster execution time is more desired than reducing the workload on the human operator, so directive behavior is more applicable to improving team efficiency. We note that instituting a time-factor for completion of a scenario though only increases performance by 12.5% on average, but increases workload by 18.5%. In transactional leadership styles, we want to minimize workload (and thus human error), by allowing individual agents to achieve individual tasks. We have shown that this is achievable through the use of behaviors associated with the transactional leadership style.



(a)



(b)

Figure 3. (a) Comparing performance values for the directive and transactional leadership styles. (b) Comparing workload values for the directive and transactional leadership styles.

5. CONCLUSIONS

In this paper, we have discussed the linkage between human leadership styles and human-robot interaction scenarios. We have adapted a leadership paradigm to employ different styles given the various situational contexts possible. Future efforts will focus on validating and comparing the other leadership styles of transformational and empowering, as discussed previously. By utilizing practices found in human relationships, we hope to improve our ability to design human-robot systems for inclusion into our everyday lives.

6. ACKNOWLEDGEMENTS

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